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Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review

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ABSTRACT

Biomass supply chain optimisation is essential to overcome barriers and uncertainties that may inhibit the development of a sustainable and competitive bioenergy market. The number of research papers presenting optimisation models in the field of bioenergy systems rises exponentially. This paper gives an overview of the optimisation methods and models focussing on decisions regarding the design and management of the upstream segment of the biomass-for-bioenergy supply chain. After a general description of the supply chain and the decisions coming along with the design and management, all selected publications are classified and discussed according to (1) the mathematical optimisation methodology used, (2) the decision level and decision variables addressed and (3) the objective to be optimised.

This classification allows users to identify existing optimisation methods or models that satisfy specific requirements. Moreover, the factual description of the presented optimisation methods and models points to opportunities for development of an integrated, holistic approach to optimise decisions in the field of biomass supply chain design and management. Such approach must be based on the consideration of the interrelationships and interdependence between all operations in the entire biomass-for-bioenergy supply chain.

Contents

Abbreviations: LP, linear programming; IP, integer programming; MILP, mixed integer linear programming; NLP, non linear programming; MoMILP, multiobjective mixed integer linear programming; MISP, mixed integer stochastic programming; REC, regional energy clustering; GA, genetic algorithm; PSO, particle swarm optimisation; BHBF, binary honey bee foraging; SQP, sequential quadratic programming; MCDA, multicriteria decision analysis; MADA, multiattribute decision analysis; MODA, multiobjective decision analysis; LCA, life cycle analysis; EIO, economic input–output; AHP, analytic hierarchy process

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1. Introduction and problem statement

The potential of alternative and renewable energy sources to reduce society's dependency on fossil fuel and to mitigate climate change is increasingly investigated [1]. Bioenergy is expected to play a dominant role because biomass as its primary product is a versatile energy source that can be stored and converted to energy on-demand [2]. However, the discontinuous availability and the relatively high maintenance and logistics costs still compromise the economic viability of biomass for large scale energy production and commercialisation [6]. Furthermore, criticism rises about the threat for food security and for rising food prices caused by the use of biomass from food crops for producing bioenergy. Also the ecological and environmental damages associated with large-scale biomass production and the inefficiency of bioenergy production due to the low energy content of the source biomass are currently non-resolved issues [7]. It can be anticipated that the role that bioenergy will play in the future 'global mix of energy supply' will depend upon the extent to which several barriers or constraining factors inhibiting international trade as well as a sustainable and efficient production of biomass resources can be overcome [7].

One of the most important *barriers* to the development of a strong bioenergy sector is the cost of the biomass supply chain [2] since handling and transport of biomass from the source location to the conversion facility induce a variety of economic, energetic and environmental implications [5]. Obviously, high costs oppose market penetration and inhibit fair competition with the traditional energy sources like fossil fuels [8]. Beside these barriers, also *uncertainties* regarding the biomass supply, transportation, logistics, production, operation, demand and price hamper the performance of biomass supply chains [9]. To overcome all these barriers and uncertainties *biomass supply chain optimisation* is essential [7]. Optimisation refers to (a) the choice of highly productive non-food crops with high yields; (b) the co-ordination of transportation, pre-treatment and storage at operational, tactical and strategic level; and (c) the use of advanced efficient biomass-for-bioenergy conversion technologies to enable relevant reductions in environmental and biomass production costs [6,7]. Such optimisation can be the subject of operations research.

The number of research papers reporting the use of optimisation methods and models in the field of bioenergy systems is rising [6,11–17]. With this paper we present an overview of the optimisation methods and models focussing on the design and management of biomass-for-bioenergy supply chains. To contribute to a clear understanding of the methods and models, Section 2 introduces the structure of a typical upstream biomass-to-bioenergy supply chain highlighting the biomass handling operations and the interrelationship and interdependence between the operations. Also, Section 2 portrays the typical decisions and the corresponding time spans considered in supply chain design and management. The classification approach (Section 3) is developed to allow candidate users to identify optimisation methods or models that satisfy their specific requirements. Based on this approach, the selected publications are classified and the methodologies are described in Section 4. Additionally, similarities and differences between the optimisation methods can be deducted from this factual description. This analysis results in the definition of opportunities for the future development of an integrated, holistic approach to support the development of an economic, energetic, social and environmental sustainable bioenergy network (Section 5).

2. Biomass supply chain management

2.1. Biomass-for-bioenergy supply chain

In biomass-for-bioenergy supply chains, three major chain segments can be distinguished. The upstream segment covers the operations from biomass production to the delivery to the conversion facility. Usually, the conversion to bioenergy is considered as a black box operation with input of biomass and output of bioenergy and by-products. The midstream segment considers the conversion process itself. The downstream segment encompasses the storage of bioenergy and its distribution to customers [10].

Six operations can be distinguished in the upstream segment, i.e. biomass production–harvest–collection–pre-treatment–storage–conversion to bioenergy [2,8,10–12]. In this context, conversion to bioenergy is considered as a black box with input of biomass and output of bioenergy (and by-products). These six operations serve to deal with the typical characteristics of biomass (e.g. spatial fragmentation, seasonal and weather related variability, high moisture content, low energy content, low bulk density) which differentiate the biomass supply chain from more traditional supply chains [11]. All these operations occur at biomass production sites or in facilities connected through transport and transhipment infrastructure. Fig. 1 presents the generic, upstream biomass supply chain segment indicating the possible

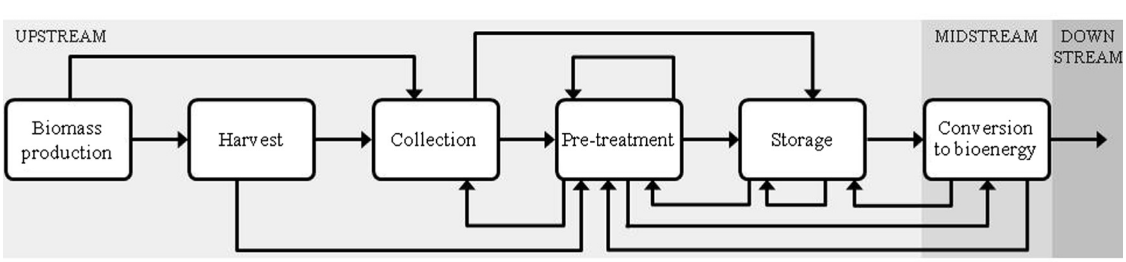

Fig. 1. Flow chart representing the interrelationships and interdependencies of operations in the biomass supply chain (Block = operation, Arrow = possible transport link between operations) [14].

product flows between the operation facilities. The arrows in Fig. 1 also point to the huge interrelationships and interdependences between all operations [6,7,13]. Not only do upstream decisions affect the later operations in the chain, but also the choice of biomass conversion technology, its size and location co-determine the type and sequence of all previous operations. This is due to the requirement that the biomass resources must be delivered at the conversion facility at the correct time, in the correct quantity and in the desired shape, size and quality [13]. In addition, biomass supply chains need to be robust and flexible to be able to adapt to changes related to the weather, competing usage and perishability of biomass and market conditions [11].

2.2. Decision making levels in biomass supply chain management

Supply chain management is defined as “the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities” [15]. In this context, logistics is “that part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers’ requirements” [15].

As highlighted in the reviews of Bravo et al. and Wee et al. [7,8], a variety of variables influences a range of decisions to be made during biomass supply chain management (e.g. choice of biomass type, of storage capacity and location, of pre-treatment technology and location, of transport mode, and of conversion location, technology and capacity, etc.). Moreover there is a complex hierarchy in the decision making to be taken into account [9,11]. Three main decision making levels exist in supply chain management: i.e. the strategic level, the tactical level and the operational level [9,11]. The *strategic decision making level* refers to long term, usually investment intensive decisions which may need revision after several years, pertaining to the design of the biomass supply network (i.e. decisions regarding sourcing, procurement of biomass, allocation of biomass between facilities, location and capacity of intermediate storages and location, size and technology of conversion facilities) [9,11,16]. The *tactical decision making level* addresses medium term (monthly) decisions usually spanning between six months and one year and limited by the established strategic decisions [9,11,16]. Tactical decisions concentrate on the logistics planning considering fleet management (e.g. mode of transport, shipment size, routing, and scheduling), selection of collection, storage, pre-treatment and transportation methods and inventory planning (e.g. how much to order, when to order, safety stocks) [9,11,16]. Finally, the *operational decision making level* tackles short term (weekly, daily or even hourly) decisions limited by the tactical decisions concentrating on inventory planning, vehicle planning and scheduling to ensure continuous and/or efficient operation of the plants and other processes in the supply chain [9,11,16].

3. Materials and methods: Classification framework

Seventy-one scientific publications (published between 1997 and 2012) are found and reviewed with a focus on the methods and models used to optimise strategic, tactical and/or operational decisions in the upstream segment of the biomass-for-bioenergy supply chain. The involved models are assessed and compared in terms of (1) the mathematical optimisation methodology applied, (2) the decision level and corresponding main decision variables addressed and (3) the objective to be optimised. The publications are briefly delineated in the corresponding section (i.e. class) in

Table 1
Main decision variables considered at each decision making level in supply chain management.

Decision level	Strategic	Tactical	Operational
Decision variables	Facility: – Location – Capacity or size – Technology or type	Inventory planning: – How much to harvest – When to harvest – Inventory control	Inventory planning: – Day-to-day inventory control
	Biomass: – Sourcing – Allocation between facilities	Fleet management: – Transport mode – Shipment size – Routing – Scheduling	Fleet management: – Vehicle planning – Scheduling

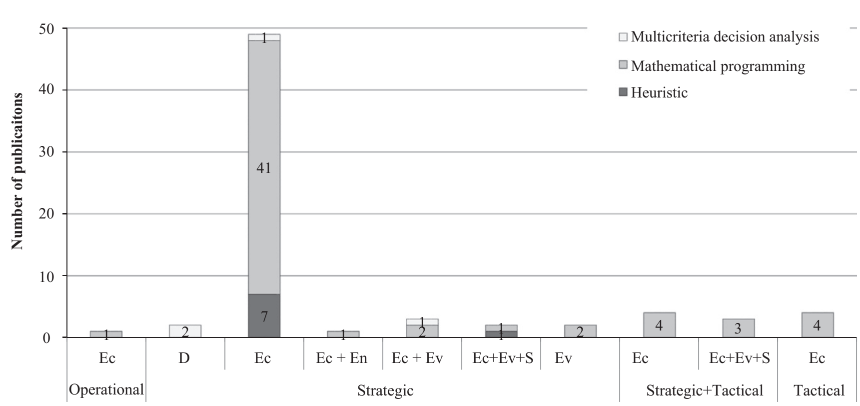

Fig. 2. Distribution of publications according to the three classification levels (Ec = Economic objective, D = Distance, En = Energetic objective, S = Social objective, Ev = Environmental objective).

which they are grouped according to specialties addressed in the method or model and ranked according to increasing complexity.

To facilitate the assessment and comparison of the methods and models, first the publications are classified according to the main *mathematical optimisation methodology* applied. Three groups of methodologies are distinguished: (1) mathematical programming, (2) heuristic approaches and (3) multicriteria decision analysis. Mathematical programming approaches, like linear programming (LP) and mixed integer linear programming (MILP), determine the values of the decision variables that optimise (maximise or minimise) an objective function among all sets of values that satisfy the given constraints [17]. Heuristic approaches, like genetic algorithms (GA), search for satisfactory (i.e. local), but not necessarily global optimal solutions to reduce runtimes [6,18]. Also multicriteria decision analysis (MCDA) methods are considered since their use is increasingly reported in publications dealing with decision making for sustainable energy provision [19]. If a publication reports about a combination of mathematical programming or heuristics with multiobjective optimisation techniques, the publication is discussed in the section about mathematical programming or heuristics to keep consistency in the description.

Second, the publications are classified according to the *decision making level*(*s*) at which they are applicable. Because each of the decision levels refers to a different time scale, different types of decisions have to be considered [11,16]. Therefore, the decision variables (binary, integer and/or continuous) included in each publication are evaluated against the main decision variables defined for each decision level (Table 1). These decision variables are the variables of which the best value is to be determined while solving the optimisation problem (i.e. objective function) satisfying the restrictions in the system. Table 1 was elaborated based on the description of the decision levels in Section 2.2.

Finally, publications are classified according to the *objective type* of the optimisation problem. In an optimisation problem the objective or goal refers to the problem dimension/aspect which has to be maximised or minimised taking into account specified criteria [17]. From the reviewed literature a distinction can be made between economic (e.g. transportation cost, net present value, risk on investment), energetic (e.g. energy return, energy use), environmental (e.g. CO_2 emissions, greenhouse gas emissions, carbon footprint, global warming potential) and social (e.g. amount of jobs) goals.

4. Results and discussion

4.1. Classification results

Fig. 2 presents the distribution of the selected publications according to the applied optimisation methodology, the decision level and the objective type. It is clear that optimisation of the economic objectives is most frequently reported about and mathematical programming is most present as optimisation technique. Also, most publications present optimisation models to optimise long term, strategic decisions.

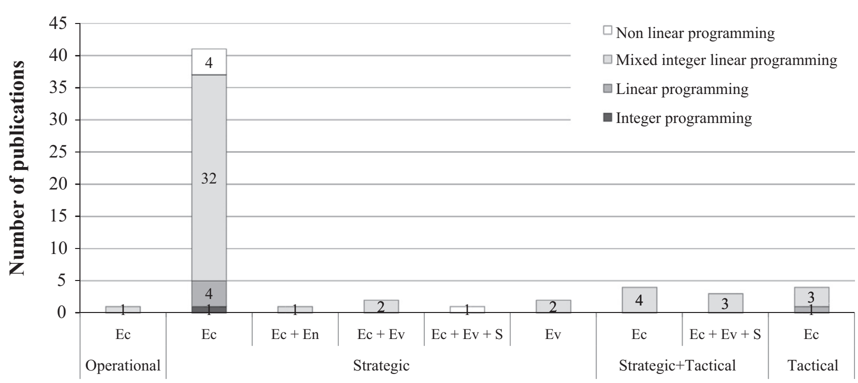

Fig. 3. Distribution of the publications applying mathematical programming according to the mathematical programming technique, the decision level and objective type (Ec=Economic objective, En=Energetic objective, S=Social objective, Ev=Environmental objective).

Table 2
Publications presenting linear programming models with identification of the decision level, objective type and decision variables considered in the model.

Publication	Decision level	Objective	Strategic decision variables					Tactical decision variables	
			Facility			Biomass		Fleet management	Inventory planning
			Location	Type	Size	Sourcing	Allocation		
Alfonso [20]	S	2	x	x					
Frombo [21]	S	1			x	x			
Panichelli [22]	S	2	x				x		
Perpiña [23]	S	2	x						
Cundiff [24]	T	3							X

S=Strategic decision level.
T=Tactical decision level.
1=Minimise overall costs.
2=Minimise transportation costs.
3=Minimise greenhouse gas emissions.

Table 3
Publications applying mixed integer linear programming for strategic decision making with identification of the decision level, objective type and decision variables considered in the model.

Publication	Decision level	Objective	Strategic decision variables					Other
			Facility			Biomass		
			Location	Type	Size	Sourcing	Allocation	
Akgul [27]	S	1	x		x	x	x	Number of transport units
Aksoy [28]	S	6	x				x	
An [29]	S	2	x	x	x		x	
Andersen [30]	S	3	x	x	x		x	
Bowling [31]	S	2	x					
Chen [32]	S	1	x		x	x	x	
Dal Mas [33]	S	2 or 5	x		x	x	x	Profit and financial risk
De Campos [34]	S	1	x		x	x	x	
De Mol [35]	S	1	x	x		x		Transport mode
Diekema [36]	S	1+/2+/4+/8+/9+/10	x	x		x	x	Transport mode
Dunnett [37]	S	1	x		x	x	x	Transport mode
Freppaz [38]	S	1	x		x	x	x	
Frombo [39]	S	1	x	x	x	x	x	
Geijzenforffer[40]	S	1,2,4,8,9 or 10	x				x	Transport mode
Giarola [41]	S	3 and 7	x	x	x	x	x	Transport mode
Huang [42]	S	1	x		x	x	x	
Kanzian [43]	S	6	x			x	x	
Kim [44,45]	S	2	x	x	x		x	Amount of intermediate product for energy input
Lam [46]	S	7					x	
Leduc [47–49]	S	1	x		x		x	
Marvin [50]	S	3	x		x	x	x	
Mele [51]	S	3 and 7	x		x	x	x	Transport mode
Natarajan [52]	S	1	x	x	x		x	
Papapostolou [53]	S	2				x		
Parker [54]	S	2	x	x	x		x	
Rauch [55]	S	1	x	x				
Srisuwan [56]	S	2					x	
Tittman [57]	S	2	x	x	x		x	
Tursun [58]	S	1	x	x	x		x	
Vlachos [59]	S	1	x				x	
Walther [60]	S	3	x	x	x		x	
Wang [61]	S	1	x		x		x	Transport mode
Zamboni [62,63]	S	1 and 7	x		x		x	Transport mode

S = Strategic decision level.
1 = Minimise overall costs.
2 = Maximise overall profit.
3 = Maximise net present value.
4 = Maximise financial revenue.
5 = Minimise risk on investment.
6 = Minimise transport cost.
7 = Minimise greenhouse gas emissions.
8 = Maximise energy return in the conversion facility.
9 = Minimise energy use in the supply chain.
10 = Maximise net energy profit.

4.2. Mathematical programming

Mathematical programming involves the development of mathematical models that represent real-world situations and can be used to determine the optimal outcome [17]. In general, a mathematical programming model involves an objective function, decision variables and constraints [17]. This implies that the values of the decision variables are determined in a way that the objective function is optimised while the values satisfy the restrictions put forward in the constraints [17]. In the 59 publications applying mathematical programming, differences in the specific characteristics of the variables, objective function and constraints lead to four distinct methods: linear programming (LP), integer programming (IP), mixed integer linear programming (MILP) and non linear programming (NLP). Fig. 3 shows the distribution of the 59 publications according to the four mathematical programming techniques, the decision level and the objective type. Among the mathematical programming techniques, mixed integer linear programming is the most frequent optimisation technique and is applied at all decision levels. In contrast, non linear programming and integer programming are only applied to optimise strategic decisions. Furthermore, economic objectives are addressed in each mathematical programming model.

4.2.1. Linear programming

Linear programming models are mathematical programming models having a linear objective function and linear constraints. Table 2 lists the publications presenting or applying LP models to optimise decisions in the upstream biomass supply chain design or management.

Several authors rely on the algorithm of Dijkstra to determine the shortest path between biomass production sites and conversion facilities [25]. Perpiña et al. [23] apply the closest facility function of geographic information system (GIS) software (based on the Dijkstra algorithm) to calculate the transportation time, the transportation distance and the transportation costs between all

biomass production sites and potential conversion sites. These results are evaluated to identify the optimal location of bioenergy facilities in the Valencian Community. Panichelli and Gnansounou present a GIS-based approach to determine the optimal allocation of biomass to torrefaction plants and the optimal location for gasification facilities considering resource competition between facilities and a significant variability in biomass farmgate price [22]. The optimal location to construct gasification facilities is defined by minimising the marginal costs related to the supply of torrefied wood to the gasification plants (i.e. delivery cost, processing cost, storing cost and transportation cost) [22]. Then, the allocation of biomass to the torrefaction plants is optimised by applying the BIOAL algorithm [22] in which the shortest path between forest sites and torrefaction facilities is calculated with the simplified Dijkstra algorithm. Alfonso et al. [20] present a modular methodology to quantify and characterise the biomass resources, to optimise the locations of conversion facilities from logistics point of view and to analyse basic economic, technical and CO_2 savings of the different energy use options. The computation and optimisation module aggregates the five other modules (i.e. biomass resource module, demand module, logistics module, technology characterisation module, environmental module) and defines in a first step a list of best conversion facility locations according to minimum transportation cost (i.e. LP) [20]. In the second step, optimisation is based on user criteria (e.g. economic suitability and CO_2 savings) taking into account the results provided by a biomass resource module, a demand module and a technology characterisation module [20]. To consider costs regarding felling and processing, facility installation and maintenance and energy sales at the current market price on top of the costs related to biomass transportation, Frombo et al. present an LP model expressing these costs as a function of the annual harvested biomass quantity and the plant capacity, constrained by the forest biomass collection to prevent species extinction and by the continuity equation at the energy plant [21].

As mentioned in the introduction, *uncertainty* is one of the hurdles hampering the development of a sustainable bioenergy network [9]. Cundiff et al. consider uncertainty in biomass production levels while optimising the design of storage facilities and arranging transportation issues in the biomass delivery system [24]. This supply uncertainty is assumed to be related to the weather conditions during the actual growing of the crop and during the harvesting month. Therefore, the authors define four weather scenarios by combining good and poor weather conditions during crop growth with good and poor weather conditions during harvest. A multi-stage LP model determines the cost-optimal monthly shipment of biomass between facilities. Also a storage capacity expansion schedule is assessed for each producer considering monthly harvests for each of the four possible weather scenarios, and storage and transport of biomass from on-farm storage locations to centrally located conversion facilities [24].

4.2.2. Integer programming

Mathematical models are considered to be integer programming models when all of the decision variables are restricted to be integers. In our set of publications, only Judd et al. [26] present an IP model in the field of biomass-for-bioenergy supply chain optimisation. Their IP model minimises the transportation and storage costs of round bales by optimising the location of storage facilities and the allocation of biomass from the farm to these facilities [26]. Two binary (integer) variables define whether a farm is selected as a storage facility (i.e. location) and whether a farm uses a storage facility at another site (i.e. allocation) [26].

4.2.3. Mixed integer linear programming

Mixed integer linear programming models combine the characteristics of the mathematical models described above, i.e. some (or all) decision variables are integers and the objective function and all constraints are linear. Because a large number of such models have been found, the corresponding publications are categorised and described according to the decision level.

4.2.3.1. Strategic decision making. Strategic decision making refers to long term, often investment intensive decisions usually concentrating on the design of the supply network [9,11,16]. Table 3 lists the publications presenting MILP models to optimise strategic decisions in the field of the upstream biomass supply chain design and management.

Due to the interaction between biomass logistics (i.e. allocation) and the design of the supply network (i.e. facility location), decision makers and investors frequently want to identify the optimal facility locations (whether or not in combination with the capacity and technology) simultaneously with the determination of the optimal flow of biomass (and eventually bioenergy) among the various nodes of the network [59]. Published approaches tackling strategic decisions in the field of biomass supply chain optimisation describe the upstream biomass supply chain as a network structure in which nodes correspond with source locations, collection sites, transhipment sites, pre-treatment sites and/or conversion sites while arcs correspond with the product flow and transport operations [31,35,59]. Then, a mixed integer linear programming (MILP) model is used to optimise the network structure and the annual flows of biomass according to a specified economic, energetic and/or environmental objective with the mass balances, capacities and demands as restrictions [31,35,59]. In this “standard” MILP model binary variables determine whether or not a facility is constructed at a certain site and continuous decision variables are related to the amount of biomass (or bioenergy) flowing from one node to another in the network structure [31,35,59]. This type of MILP model is applied to the cost optimal facility location and organisation of woody biomass flow in Alabama, USA [28], biodiesel supply chains based on biomass production by small farmers in Brazil [34], the lignocellulosic biomass-to-bioethanol supply chain in the USA [50], the production of methanol in wood gasification plants in Austria [47], biodiesel production in India [48], the ethanol production based on lignocellulosic biomass in Sweden [49] and the methanol and combined heat and power (CHP) production in Eastern Finland [52]. In contrast to the optimisation of the location of conversion facilities as described in the previous papers, Rauch et al. apply a similar MILP model to determine the cost optimal arrangement of storage facilities characterised by the chipping technology and chipping volume processed, to optimise the supply from the forest to a total of 28 combined heating facilities [55]. In order to optimise the number of transport units required for the transfer of products between regions and local delivery, Akgul et al. [27] include some extra integer variables determining the number of transport units. The integers come on top of the binary variables determining the location and size of bioethanol production facilities and the continuous variables defining the biomass and bioethanol flows between regions. To reduce the problem size and computational requirements when solving network problems of large scale, Akgul et al. [27] introduce a neighbourhood flow representation in their MILP. Two different configurations are defined, i.e. 4N and 8N in which the flow directions differ to and from a region [27]. This means that in the 4N and 8N configurations, the material (biomass or biofuel) flow directions to and from a region (cell) are mutual with the four and eight neighbouring regions (cells), respectively [27].

Embedding the MILP model in a *GIS-software* allows the use of GIS functions for the characterisation of the problem and/or the computation of the parameters involved in the problem formulation. This is applicable to the determination of the potential facility locations based on a specific set of criteria (e.g. population, access to major highways and railroads and existence of a similar facility)

and to the calculation of the least cost paths from all source origins to all potential conversion facility locations [38,39,54,57]. These data are then used in the "standard" MILP model in which binary variables determine whether or not a conversion facility is constructed at a potential conversion facility location and continuous decision variables determine the amount of biomass transported between biomass supply points and conversion facilities [54] and also the capacity of the opened conversion facility [38,39,57]. Kanzian et al. [43] combine this "standard" MILP model with a GIS to determine the optimal material flows and expected costs at plant level for different demand scenarios and supply options and to demonstrate the differences between direct flow and flow via a storage facility. Geijzenforffer et al. [40] combine the MILP Bioloco [64] with a GIS, which makes it possible to compute the expected biomass supply and the transportation distance and to assess the spatial impacts of the feedstock requirements.

Even though economic, energetic, environmental and social concerns simultaneously affect the decisions to be made in supply chain management, most optimisation models concentrate on the optimisation of economic issues (Fig. 2). To circumvent this limitation, several authors apply Pareto optimisation to identify the set of Pareto alternatives representing the optimal trade-off between the economic and environmental objectives described by MILP models [51,62,63]. In these MILP models continuous variables can denote production rates, daily impacts, costs, material flows [62,63] and capacity expansions [51], while binary variables define whether or not transportation links are established, and whether or not conversion facilities and terminals are opened in a certain region [51,62,63]. The integer variables in these *multi-objective* MILP (MoMILP) models determine the number of transport units of each type to be selected [62,63] and the number of conversion facilities and storage facilities to be selected [51]. In contrast with Geijzenforffer et al. [40], Diekema et al. [36] combine the MILP model Bioloco [64] with goal programming techniques to allow the optimisation of biomass flow and conversion facility location and technology according to a user defined combination of the objectives (i.e. minimise overall cost, maximise overall profit, maximise financial revenue, maximise energy return, minimise energy use or maximise energy profit).

Although the influence of *time varying characteristics* is very clear in tactical and operational decision making, also long term decisions are influenced by the temporal variability in supply of biomass and the growing energy demand. Therefore, multi-period and/or multi-stage MILP arise to minimise the overall system cost throughout the planning horizon, which is divided into multiple time periods [29,30,41,42,58,61]. This implies that decisions regarding the optimal facility locations and biomass flows are made for each time period. Also in this MILP binary decision variables determine whether or not a facility is opened and continuous variables determine the amount of biomass source flow and produced bioenergy [29,30,41,42,58,61]. The growing demand is then specified for each time period in the planning horizon [29,30,41,42,58,61]. Srisuwan and Dumrongsiri [56] describe a multi-period MILP to maximise the profit and productivity from planting main crops like cassava and sugarcane and to minimise the transport cost for transporting the harvested crops from the biomass production site to the conversion facility. This model results in an optimal schedule of biomass production for each unit of land in each time period. To include time variation, Dunnett et al. [37] present a combined production and logistics MILP to investigate cost-optimal configurations of the lignocellulosic bioethanol supply chain for a range of technological, system scale, biomass supply and ethanol demand distribution scenarios specific for European agricultural land and population densities. In comparison to the MoMILP model of Zamboni et al. [62,63], the MoMILP model of Mele et al. [51] introduces different time intervals which allows the model to consider time variation in sugar cane supply, energy demand and transportation cost.

Besides time variability, also *uncertainties* regarding the biomass supply, transportation, logistics, production, operation, demand and price hamper the performance of biomass supply chains. To include uncertainties in future developments, Walther et al. [60] extend a multi-period, multi-stage MILP into a scenario based planning approach applying different objective functions representing risk attitudes of decision makers. Other authors include uncertainties regarding the biomass supply, transportation, logistics, production, operation, demand or price by expanding deterministic MILP models as described so far with stochastic techniques [32,33,44,45]. In the two-stage mixed integer stochastic programming (MISP) model of Chen and Fan [32] the binary variables determine the location of the storage and conversion facilities and continuous decision variables define the size of the conversion facility and the biomass and bioenergy flow between facilities under a specified scenario. Then, this MISP model is used to determine the cost optimal facility locations and feedstock resource allocation taking into account potential future feedstock supply and fuel demand uncertainties [32]. Furthermore, Dal Mas et al. [33] add a stochastic formulation of price uncertainty to the MoMILP of Zamboni et al. [62,63] to include the effect of uncertainty on biomass and bioethanol prices. Kim et al. [44,45] first extend the "standard" MILP with some extra continuous variables to determine the amount of intermediate product to be consumed for utility energy at a conversion facility of a certain type at a certain location. This MILP is then expanded to a two-stage MISP to take into account the uncertainty in supply amount, market demands, market prices and processing technologies by maximising the expected profit over the different scenarios [45].

In contrast with previous publications in which the MILP model is used to determine optimal facility locations and biomass flows, Lam et al. [46] present a new procedure for Regional Energy Clustering (REC) to define the biomass flows from the available source points to the target sink points with minimum carbon footprint. In this procedure the clusters are formed by the MILP model based on the priority that the residual bioenergy imbalance within the newly formed clusters is minimised (preferably zero) [46]. Also the MILP model of Papapostolou et al. [53] deviates from the ideas of the previous MILP models. Their MILP maximises the total value of the biomass supply chain by optimising the quantities of biomass being locally cultivated, imported and exported and the quantities of biofuels produced for the domestic market, imported and exported. Therefore, the MILP model includes technical constraints (e.g. land use and water use) as well as demand and mass balance constraints.

4.2.3.2. Tactical decision level. Tactical decisions are constrained by the established strategic decisions and cover medium to short term decisions regarding inventory planning (e.g. how much to harvest, and when to harvest) and fleet management (e.g. mode of transport, shipment size, routing, and scheduling). Table 4 lists the publications presenting MILP models to optimise tactical decisions in the upstream biomass supply chain.

Although the publications address different types of tactical decisions, all authors present a multi-period MILP model with a monthly time period to include the biomass production and/or bioenergy demand dynamics over the annual cycle (i.e. time horizon). Dunnett et al. [65] focus on the optimisation of operational processing and of the harvesting and logistics task schedule given the system superstructure, the dynamic fresh weight, harvest moisture content and analytical ambient drying rates. In the MILP model, integer variables determine decisions regarding

Table 4
Publications applying mixed integer linear programming for tactical decision making with identification of the decision level, objective type and decision variables considered in the model.

Publication	Decision level	Objective	Tactical decision variables				
			Fleet management				Inventory planning
			Transport mode	Shipment size	Routing	Scheduling	
Dunnett [65]	T	1	x			x	X
Flisberg [66]	T	2	x		x	x	X
Gunnarsson [67]	T	1			x	x	X

T = Tactical decision level.
1 = Minimise overall costs.
2 = Maximise overall profit.

Table 5
Publications applying mixed integer linear programming for strategic and tactical decision making with identification of the decision level, objective type and decision variables.

Publication	Decision level	Objective	Strategic decision variables					Tactical decision variables	
			Facility			Biomass		Fleet management	Inventory planning
			Location	Type	Size	Sourcing	Allocation		
Ekşioğlu [70,71]	S+T	1			x	x	x	x	X
Tembo [72]	S+T	2	x		x	x	x	x	X
You [73–75]	S+T	1, 3 and 4	x	x	x		x	x	X
Zhu [76]	S+T	5	x		x	x	x	x	X

S = Strategic level.
T = Tactical level.
1 = Minimise overall costs.
2 = Maximise net present value.
3 = Minimise greenhouse gas emissions.
4 = Maximise amount of jobs.
5 = Maximise overall profit.

the selection of components and the number of component units installed (e.g. which harvester, truck, heating plant, etc. to be used with which capacity). Binary variables assign tasks to optimise the operation schedule within the derived structure (e.g. which operations to apply and when) [65]. Gunnarsson [67] apply the MILP model to decide when and where forest residues have to be converted into chips, and how residues are to be transported and stored in order to satisfy the contracted demand at the saw mill. Therefore, continuous variables determine the biomass flows from harvest areas and saw mills to heating plants in each time period and binary variables determine whether forest residues are forwarded or chipped, whether a saw mill has been contracted and whether a terminal is used in a certain time period [67]. This MILP model considers chipping capacity, storage capacity, demand and transportation costs related to each time period. Finally, Flisberg et al. [66] focus on the optimisation of inventory planning at the terminals to support the choice of chipping technology and location and the route to the heating plants. The MILP contains two different types of variables for inventory at supply points: (1) inventory of volumes that are not purchased yet (these are optional and hence not chipped) in a certain time period and (2) inventory of volumes that have been purchased in a certain time period [66]. To enable the optimisation in each time period, Flisberg et al. [66] define the costs related to the purchase of biomass, inventory and transportation for each time period considered in the model. This enables the user to identify the costs related to each stage in the supply chain in each time period.

4.2.3.3. Operational decision level. Operational decisions are short term (weekly daily or even hourly) decisions concentrating on inventory planning, vehicle planning and scheduling to ensure continuous operation of the conversion facilities and other processes in the supply chain [9,11,16]. From all selected publications presenting optimisation models in the field of biomass supply chain management, only one addresses decisions in the operational realm, i.e. van Dyken et al. The main issue considered in this publication is to keep track of the changes in quality and appearance of each product after a specific operation [68]. The presented MILP is an extension of the optimisation model “eTransport” which is designed for the planning of energy systems with multiple energy carriers and technologies taking into account the flow of energy from one node to another [69]. In “eTransport”, the operational model minimises the overall cost of the diurnal operations for a given infrastructure and for given energy loads [68]. ”eTransport” consists of a combination of submodels for each energy carrier and for each conversion component [68]. To include the changes in flow volume and moisture content, van Dyken et al. add biomass submodels representing the supply, processing, storage and demand operations in the biomass supply chain [68]. These submodels include LP formulations to define the constraints (e.g. restricted difference between input and output moisture content in a dryer, amount of biomass burned in the dryer) and to keep track of the variations in the moisture content and the impact on other biomass properties [68]. As a result, the model is able to economically optimise the operations (transport, storage and pre-treatment) of the biomass supply system for a whole

year on a weekly basis allowing the implementation of long-term (drying) functions in operational optimisation [68].

4.2.3.4. Strategic and tactical decision level. Because the design of the supply network involves long term decisions while logistics management requires medium to short term decisions, several authors present a MILP to identify size and location of facilities simultaneously with the optimisation of inventory planning and/or fleet management. Table 5 lists the publications presenting MILP models addressing such simultaneous optimisation of strategic and tactical decisions.

To address strategic decisions as well as tactical decisions, the proposed multi-period MILP models consider binary variables determining whether or not a facility (with a certain capacity) is opened at a certain location and continuous variables determining the amount of biomass harvested and the amount of biomass shipped and inventoried between facilities during a time period (e.g. month) within a time horizon (e.g. year) [70–72]. In the model developed by Tembo et al., "within period dynamics" are applied to determine the tactical decisions about biomass flow and strategic decisions regarding the location and size of conversion facilities endogenously assuming that all investments take place at the beginning of a 15-year cycle [72]. In addition, the MILP model of Ekşioğlu et al. [70] also determines whether or not a collection facility with a certain capacity is opened at a site. The seasonal dependency of biomass supply and land competition is included in the constraints of the MILP model [70]. This MILP model has been more recently extended to include decisions about the transportation modes [71]. Also, the MILP model presented by Zhu et al. [76] integrates strategic decisions on the switch grass supply chain and tactical decisions on the operation schedule. Therefore, the MILP contains decision variables to determine the number, locations and sizes of storage and conversion facilities, to prescribe harvesting modes, capacities, and man power, and to determine transportation modes, capacities, and fleet. To include the tactical decisions, extra decision variables are added to define the direction and quantity of switch grass transportation flows, to prescribe methods of residues handling and the corresponding transportation flows, and to schedule agricultural sector-wide paradigm shifts for the harvesting team and transportation fleet and their maintenances [76]. In contrast with the previous models, You et al. integrate the economic objective (i.e. minimising the net present value) with life cycle analysis (LCA) and regional economic input–output (EIO) analysis through a multi-objective optimisation scheme to include an environmental objective measured by life-cycle greenhouse gas emissions and a social objective measured by the number of local jobs resulting from the construction and operations of the cellulosic biomass supply chain [73–75].

4.2.4. Non linear programming

A mathematical programming model is called non linear if the objective or some of the constraints contain non linear functions. Table 6 lists the publications presenting non linear programming (NLP) models to optimise the upstream biomass supply chain.

The MILP models described in Section 4.2.3 deal with the optimisation of the biomass supply chain, but do not consider optimisation of the conversion process itself. Corsano et al. [79] add non linear mass balance, time and design constraints for the different stages (i.e. inoculation preparation, fermentation, centrifugation,

Table 6
Publications applying non linear programming with identification of the decision level, objective type and decision variables considered in the model.

Publication	Decision level	Objective	Strategic decision variables					Other	Tactical decision variables	
			Facility			Biomass			Fleet management	Inventory planning
			Location	Type	Size	Sourcing	Allocation			
Bai [77]	S+T	1	x					Plant design Footprint	x	
Bruglieri [78]	S	1	x	x						
Corsano [79]	S	2	x				x			
Čuček [80]	S	1, 3 and 4					x			
Singh [81]	S	1	x		x					

S=Strategic decision level.
T=Tactical decision level.
1=Minimise overall costs.
2=Maximise overall profit.
3=Minimise environmental footprint.
4=Minimise social footprint.

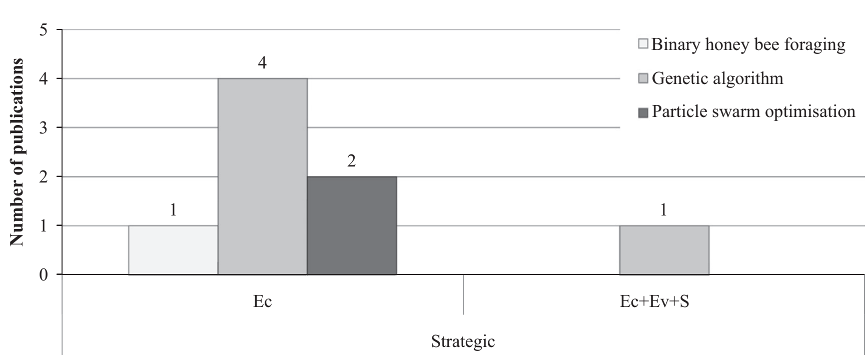

Fig. 4. Distribution of publications applying heuristics according to the heuristics algorithm, the decision level and the objective type (Ec=Economic objective, S=Social objective, Ev=Environmental objective).

evaporation and distillation) to optimise the ethanol plant design simultaneously with the supply chain. The mass balance constraints and decision variables to optimise the supply chain design are similar as the MILPs described in Section 4.2.3 in which binary variables determine the location of storage and conversion facilities and continuous variables determine the biomass flow between facilities.

Bai et al. [77] have another motivation for introducing a non linear objective function in a MILP model. They want to address conversion facility location and shipment routing decisions simultaneously including the resulting traffic congestion impact. In this NLP, binary decision variables determine the location of the conversion facility and continuous decision variables denote biomass flow and ethanol flow on any possible path. To solve this NLP model in a first stage near-optimum feasible solutions are obtained by a Lagrangian relaxation while, in a second stage, a branch-and-bound framework is applied to improve optimality [77].

The NLP model presented by Bruglieri et al. [78] optimises the planning (i.e. location and technology) of the installation of processing plant types used in the production process. The NLP is solved by an exact reformulation to a MILP. Also Singh et al. [81] apply NLP modelling to obtain the optimum location of biomass based power plants and their collection centres by minimising the collection cost in the field, transportation cost, conversion cost and collection centre radius. The NLP is solved following the Nelder Mead method [81]. Čuček et al. [80] combine a NLP model and Pareto optimisation to simultaneously maximise the economic performance and minimise environmental and social footprints. The NLP consists of continuous variables determining the biomass flow, mass balances, production and conversion constraints, cost functions, profit objective functions and carbon footprint calculations extended with continuous variables defining environmental footprints and social footprints [80].

4.3. Heuristics

While mathematical programming models seek for the optimal value of the decision variables [17], heuristic approaches will look for satisfactory, but not necessarily optimal solutions to solve complex problems in reduced runtimes [6,18]. The distribution of the publications applying heuristics to optimise upstream biomass supply management (Fig. 4) distinguishes three different heuristics algorithms; i.e. genetic algorithm (GA), particle swarm optimisation (PSO) and binary honey bee foraging (BHBF). These heuristics are known as population based heuristics which "use a population of solutions which evolve during a given number of iterations, also returning a subset of the population of solutions when the stop condition is fulfilled" [6]. Fig. 4 and Table 7 summarise the selected publications according to the framework described in Section 3.

A *genetic algorithm* mimics the process of natural evolution and allows the population to evolve under specified rules to a state that maximises the selected criteria [86]. Venema [88] apply a GA approach to solve a *p*-median problem describing the bioenergy spatial design (location-allocation) problem to optimise supply locations, conversion facility locations, domestic and commercial energy demands and energy flows. The GA uses a binary encoding of decision variables representing the candidate supply locations and candidate conversion locations. Celli et al. [83] present a GA to determine the optimal number, location and capacity of a biomass combined heat and power facility in Sardinia (Italy) by maximizing the economic benefit for private investors. The optimisation process is based on a grid subdivision of the study area which requires that the GA is integrated in a GIS to deliver all relevant information from georeferenced data [83]. Ayoub et al. [82] combine a GA with data mining techniques (e.g. fuzzy *C*-means clustering and decision tree methods) to define the optimal size of storage and conversion facilities which minimise the transportation costs, CO_2 emissions and number of workers. This result is then used in simulation models to evaluate the selected supply chain for economical and technical feasibility [82]. Besides the variety of advantages of GA (e.g. large number of continuous and discrete variables, simultaneously evaluates a large population instead of a single point, optimises non-linear, non-continuous and non-differential functions), a disadvantage of GA is that, after a certain point, the method becomes slow in finding the solution close to the global optimum [86]. To overcome this disadvantage, Rentizelas et al. [86,87] combine a GA and a sequential quadratic programming (SQP) model to economically optimise the location and size of a conversion facility and the types and quantities of biomass to be procured each year. In the first step the GA defines a very good solution near the global optimum. The solution of the GA is the starting point of the fast converging SQP model that may lead to the global optimum with high accuracy [86,87]. This procedure reduces the risk of identifying a local optimum instead of the global optimum by using the SQP model alone.

Table 7
Publications presenting heuristic approaches with identification of the decision level, heuristic methodology, objective type and decision variables considered in the model.

Publication	Decision level	Method	Objective	Strategic decision variables				
				Facility			Biomass	
				Location	Type	Size	Sourcing	Allocation
Ayoub [82]	S	GA	1, 2 and 3	x		x		
Celli [83]	S	GA	5	x		x		
Izquierdo [84]	S	PSO	4		x		x	
Reche Lopez [85]	S	PSO	5	x			x	
Rentizelas [86,87]	S	GA	6	x		x	x	
Venema [88]	S	GA	3	x				x
Vera [89]	S	BHBF	5	x		x	x	

S = Strategic decision level.
GA = Genetic algorithms.
PSO = Particle swarm optimisation.
BHBF = Binary honey bee foraging.
1 = Minimise transport cost.
2 = Minimise greenhouse gas emissions.
3 = Minimise amount of jobs.
4 = Minimise overall costs.
5 = Maximise overall profit.
6 = Maximise net present value.

Particle swarm optimisation is an evolutionary stochastic algorithm based on the social behaviour of organisms such as bird flocking and fish schooling [85]. The optimisation method is proven to be effective in multi-dimensional optimisation problems [85]. Izquierdo et al. [84] apply particle swarm optimisation (PSO) to optimise the technology type of a conversion facility. In previous models one binary variable defines the presence of one specific technology. In PSO, one discrete decision variable can be used taking any value between 1 and the number of technologies to define which technology must be applied [84]. López et al. introduce a binary PSO to determine the optimal placement and supply area of the conversion facility in which the ratio between the net present value and the initial investment is used as the fitness function for the binary optimisation algorithm [85].

Similar to PSO, *honey bee foraging* (HBF) is an optimisation algorithm inspired by the swarm behaviour of honey bees [89]. To fulfil the non-continuous problem of choosing the best location on a grid map, Vera et al. [89] adjust HBF to binary HBF (BHBF). "BHBF algorithm is potentially suitable for multi-modal problems where all the peaks above a certain height are to be discovered and also for dynamically changing environments where the position and height of peaks may shift" [89]. Also in this publication, the ratio between the net present value and the initial investment is used as the fitness function [89].

4.4. Multicriteria decision analysis

Multicriteria decision analysis (MCDA) is "a decision aid and a mathematical tool allowing the comparison of different alternatives or scenarios according to many criteria, often conflicting, in order to guide the decision maker towards a judicious choice" [90]. Depending on the type of the criteria multiattribute decision analysis and multiobjective decision analysis are distinguished. In this context, attributes are assumed to be the properties of elements of the real world geographical system [91], while an objective is a statement about the desired state of the system under consideration related to or derived from a set of attributes [91]. Table 8 summarises the characteristics of the publications applying MCDA to optimise decisions in biomass supply chain management. For completeness, the publications combining multiple objectives in their mathematical programming model (Section 4.2) or their heuristics (Section 4.3) are also included in Table 8. However, these models and methods are discussed in the corresponding sections.

Multiattribute decision analysis (MADA) is a form of MCDA in which attributes are used as classification criteria to choose the best or the most preferred alternative, to sort out alternatives that seem good and/or rank the alternatives in descending order of preference [19,91]. In spatial MADA the attributes are represented in a GIS database as criteria map layers [91]. Then, the capabilities of GIS and MCDA techniques (e.g. simple additive weighting method, ideal point methods and analytic hierarchy process) are combined to aggregate these geographical data and the decision maker's preferences into unidimensional values of alternative decisions which can be ranked or sorted [91]. Ma et al. [92] perform a land suitability analysis using overlay and buffer functions of GIS software in which economic factors and environmental and social constraints are combined using the analytic hierarchy process (AHP) method. This results in a final suitability map indicating the most suitable (highest score) zones for future development of anaerobe digesters. Also, Zhang et al. [95] apply MADA to identify the potential conversion facility locations defined according to county boundaries, county-based pulpwood distribution, population census, city and village distributions, and railroad and state/federal road transportation networks. Then, the optimal conversion facility is determined by calculating the transportation cost for each candidate facility location [95]. After ranking from smallest to largest, sufficient supply points are considered to ensure that the facility biomass demand is met.

Table 8
Publications applying multicriteria decision analysis with identification of the type of MCDA, decision level, objective type and decision variables considered in the model.

Publication	Type MCDA	Decision level	Objective	Strategic decision variables					Tactical decision variables	
				Facility			Biomass		Fleet management	Inventory planning
				Location	Type	Size	Sourcing	Allocation		
Čuček [80]	MO	S	1, 7 and 11					x		
Diekema [36]	MO	S	1,2,4,8,9,10	x	x		x	x		
Giarola [41]	MO	S	3 and 7	x	x	x	x	x		
Ma [92]	MA	S	5	x						
Mele [51]	MO	S	3 and 7	x		x	x	x		
Rozakis [93]	MO	S	4 and 7	x	x	x				
Shi [94]	MA	S	5	x						
You [73–75]	MO	S+T	1, 12 and 13	x	x	x		x	x	x
Zamboni [63]	MO	S	1 and 7	x		x		x		
Zhang [95]	MA	S	6	x						

S = Strategic decision level.
T = Tactical decision level.
MA = Multiattribute.
MO = Multiobjective.
1 = Minimise overall costs.
2 = Maximise overall profit.
3 = Maximise net present value.
4 = Maximise financial income.
5 = Minimise transport distance.
6 = Minimise transport cost.
7 = Minimise greenhouse gas emissions.
8 = Maximise energy return in the conversion facility.
9 = Minimise energy use in the supply chain.
10 = Maximise net energy profit.
11 = Maximise amount of jobs.
12 = Minimise environmental footprint.
13 = Minimise social footprint.

Shi et al. [94] present a supply-area modelling approach to determine the optimal sites for bioenergy power plants in Guangdong. The supply-area modelling approach selects locations which are surrounded by high local densities [94]. After assigning the biomass points within the supply area of a candidate site (defined by a transportation cost threshold to the candidate site), all sites are ranked according to the usable biomass in the supply area and the efficiency score calculated using a distance-decay function [94].

The interactive *multiobjective* analysis tool of Rozakis et al. [93] selects the location, capacity and technology of the conversion facility that is best adapted to the preferences and interests of the user. The DSS consists of six modules which model biomass production, harvest, transportation, conversion technologies and environmental impacts at all stages of the activity [93]. The seventh module is the optimisation module which will define the Pareto optimal solutions according to the criteria defined by the user and the results of the other modules [93]. The other multiobjective decision analysis (MODA) methods and models defined in Table 8 are described previously.

5. Conclusions

Studies dealing with alternative and renewable energy production and use indicate that by 2050 biomass will occupy a significant share (between 40 and 50%) in the renewable and alternative resources for the production of electricity, heat and transport fuels [3–5]. However, a variety of barriers and uncertainties inhibit the development of a strong, international bioenergy sector as well as a sustainable and efficient production of biomass resources [7]. The role that bioenergy will play in the future 'global mix of energy supply' will depend upon the extent to which these hurdles can be overcome. To overcome these barriers and uncertainties and enhance the development of a sustainable and competitive bioenergy market, biomass supply chain optimisation is essential. A variety of researchers has already accepted the challenge to develop and apply models to optimise the decisions regarding the design and the management of the upstream biomass supply chain. Because this resulted in a mixture of approaches, this paper provides an overview of the research developments regarding the use of optimisation methods for supply chain design and management in the field of bioenergy production.

The review shows that most publications apply mathematical programming approaches. The major part of the mathematical programming models refer to a network structure in which nodes correspond to facility locations (i.e. biomass production, collection sites, transhipment sites, pre-treatment sites, conversion sites) and arcs correspond with the product flow and transport operations. Then, most selected publications apply a MILP model optimising binary variables that determine whether or not a facility is opened at a certain site and continuous decision variables which are related to the biomass (or bioenergy) flow from one node to another given the biomass balances, capacities and demand as a restriction. This MILP model can be seen as the basis that can be extended by including other decision variables, constraints, multiple periods, multiple objectives, uncertainty in supply and demand, etc. The drawback of these mathematical programming techniques is that a large number of decision variables is required to describe complex issues like supply chains. Moreover, these methods usually require long computation times [96]. To address these shortcomings of mathematical programming methods, heuristic optimisation methods have been introduced for the optimisation of the supply chain management. Especially evolutionary heuristics like genetic algorithms and particle swarm optimization are well known as "flexible heuristics for handling difficult combinatorial optimization problems" like the problem of supply chain management [96]. With its simplicity and generality, GA seems to be an efficient technique for solving large and complex network (even non linear, non continuous and non differentiable) planning problems [86,96], while PSO has the main advantages that it is very easy to implement and only a few parameters need adjustment [85]. However, when using heuristics one has to be aware for the occurrence of local optima instead of global optima. The comparison of MILP with heuristic algorithms by Sadegheih et al. [96] indicates that the heuristic algorithms are able to obtain good quality solutions in a reasonable amount of time even for large size problems. Therefore, heuristics are generally used for operational problems which have to be solved rapidly, within seconds or minutes whereas mixed integer linear programming (MILP) methods are better for tactical and strategic planning problems which can be solved over a longer period of time, sometimes taking many hours [16]. However, this paper doesn't substantiate this conclusion because heuristics are only applied to solve strategic decisions and all tactical and operational decisions are addressed by mathematical programming models. This topic provides opportunities for profound R&D efforts. Multicriteria decision analysis usually makes use of spatial information technologies to determine and rank the suitable locations. These models are limited to the optimisation of the location of conversion facilities, but thanks to their simplicity and visualisation power they are easier to understand than the heuristic and mathematical programming approaches.

Optimisation methods are regularly combined with geographical information system (GIS). On the one hand, the GIS is used to process and visualise the input data and the results [16]. On the other hand, the functions of the GIS allow computing transportation distances, to determine shortest paths between facilities, to define potential locations to construct facilities, etc. Then, this geographic information can be applied to parameterise the optimisation model.

Sustainability of supply chains has emerged as a concern to address the potential of supply chains to take into account "the long-term risks associated with resource depletion, fluctuations in energy costs, product liabilities, and pollution and waste management [98]" [97]. This implies that sustainable supply chain management needs to integrate consideration of economical, environmental and social objectives [97]. This literature review points out that only two authors (i.e. [80,73–75]) present a multiobjective approach in which these three objectives are incorporated. Economically, these models use the determination of the total costs in the chain to define the economical sustainability. In both models, the social objective is measured by the number of local jobs. This approach seems simplistic since social sustainability also covers the integration of human rights, labourer's rights and corporate governance [97]. To address the environmental issue the existing multiobjective models focus on the minimisation of greenhouse gas emissions in the chain. However, environmental sustainability also considers "natural resources endowments, past and present pollution levels, environmental management efforts, contribution to protection of the global commons and society's capacity to improve its environmental performance over time" [97]. This analysis points to opportunities to better address the social and environmental sustainability in the existing multiobjective optimisation models. For example by incorporating the effects of legislations (e.g. EU Directive 2008/1/EC—Integrated pollution prevention and control). Especially fields of application like pollution prevention and control and waste management in which reverse logistics and closed loop supply chains are considered [99] are likely to benefit from these opportunities.

Finally, the paper shows that the presented models are usually developed for specific cases addressing a specific part of the supply chain considering specific operations at one certain hierarchical decision level. Also, most papers target the optimisation problem from

the bioenergy producer's point of view which is understandable because the energy producer is the one making the long term investments. However, the optimisation of the upstream biomass supply chain is strongly determined by the interrelationship and interdependence between all biomass supply operations and their locations (i.e. cultivation, harvesting, storage, conversion/pre-treatment and transportation) [7]. This implies that more R&D-efforts are needed to come up with more integrated, holistic approaches given equal emphasis to all operations in the entire supply chain [6].

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